Bone Health Assessment for the Clinical Evaluation of X-ray Modal Images in Patients with Osteoporosis using Deep Learning Methods

A SYNOPSIS

Submitted by

GAUTAM AMIYA

(Reg. No. 9921604003)

in partial fulfilment for the award of the degree

of

DOCTOR OF PHILOSOPHY

DEPARTMENT OF COMPUTER SCINECE ENGINEERING

SCHOOL OF COMPUTING

KALASALINGAM ACADEMY OF RESEARCH AND EDUCATION

(DEEMED TO BE UNIVERSITY)

ANAND NAGAR, KRISHNANKOIL – 626 126

TAMILNADU, INDIA.

AUGUST 2024

1. INTRODUCTION

Bones consist of interconnected collagen, calcium, and phosphorous. Typically, bones exhibit hardness, strength, solidity and thickness. However, there are instances when bones become notably fragile and susceptible to breakage, which deviates from the usual expectations, often due to medical conditions such as Osteoporosis or Osteopenia. Bone ailments encompass various illnesses or traumas that adversely affect bone health.[1] These conditions typically result in abnormalities within the skeletal structure of the human body, rendering bones prone to fractures. Fractures may occur due to either the mechanical or biochemical properties of bones, or a combination of both factors.[2]

Osteoporosis (OP) is a prevalent bone condition resulting from reduced bone mineral density [3]. Asians, in particular, face an elevated risk of developing OP, particularly after the age of 35. The elderly, particularly women who tend to live longer and may have concurrent health issues, are at a heightened susceptibility to OP. It is advisable for women aged 65 and older and men aged 70 and older to undergo regular bone density screenings [4].

Osteopenia serves as the precursor to osteoporosis (OP), characterized by a lower bone mineral density (BMD) compared to OP [5]. A diminished BMD is strongly associated with the onset of OP. The BMD examination assesses the quantity of calcium and other minerals present within the bone [6]. Higher mineral concentrations contribute to denser, sturdier bones less prone to fractures, whereas lower concentrations can lead to bone fragility and breakage. Various scanning methods such as quantitative ultrasound, single-energy X-ray absorptiometry (SEXA), Magnetic Resonance Imaging (MRI), Quantitative computed tomography (QCT), and dual-energy X-ray absorptiometry (DEXA/DXA) are available for evaluating BMD. Figure 1 illustrates sample multimodal images depicting normal and OP conditions.

It is a significant global issue that requires early detection and precise prediction. Additionally, each patient necessitates a tailored and personalized course of therapy and treatment. This approach aims to reduce the socioeconomic burden, mitigate the emotional distress experienced by patients following bone fractures, and enhance the overall management of affected individuals.

Osteoporosis, which translates to "porous bone," arises from three primary causes: A) inadequate intake of calcium, phosphorus, and vitamin D; B) hormonal imbalances, particularly estrogen deficiency in women; and C) excessive consumption of alcohol or tobacco. These factors contribute to a reduction in bone mass and strength [7]. Consequently, the risk of fractures escalates, both spontaneously and due to minor external stressors, particularly affecting the hip, wrist, and spine regions. Common symptoms of osteoporosis include height loss, forward bending, shallow breathing, and lower back pain. The likelihood of osteoporotic fractures rises with age, particularly among postmenopausal women and those over 50 years old [8]. Certain ethnic groups, such as Caucasian and Asian women, exhibit a heightened predisposition to osteoporosis. Additionally, certain medical conditions and medications increase the susceptibility to osteoporosis, including hyperactivity of the thyroid, parathyroid, or adrenal glands, bariatric surgery, hormone therapies, inflammatory bowel disease, and multiple myeloma [9].

When external force exceeds the inherent strength of a bone, there is a risk of bone fracture. This strength is determined by various factors including bone size, mass, shape, architecture, and other essential physical, chemical, and mechanical properties [10]. Common measures used to assess bone health include the T Score, Z Score, and Stiffness Index. Presently, the World Health Organization recommends the T Score obtained from DXA scans as the preferred medical assessment method due to its affordability, non-invasiveness, and portability. However, DXA scans have limitations. They may not accurately measure bone mineral density (BMD) in individuals with severe spinal conditions, abnormal spinal shapes or sizes, obesity, or calcification of the aortic valve, which can lead to narrowing [3]. Furthermore, merely assessing BMD is insufficient; understanding the structural and physical characteristics of trabecular and cortical bones is also crucial. Therefore, there is a pressing need to improve both the early detection of osteoporosis and the management, treatment, and therapy of affected individuals.

Bone mineral density is mathematically expressed as the ratio of bone mineral content within a scanned bone segment to the volume of that segment, typically measured in grams per cubic centimeter [11]. Factors such as the Stiffness Index, T-Score, Z-Score, and FRAX Score are utilized in assessing bone mineral density.

The T score compares a patient's bone density to that of a healthy adult of the same gender at 30 years old, measured in standard deviations [12]. A T score of -2.5 or lower indicates

osteoporosis, while a T score between -1 and -2.5 signifies osteopenia, and a value of -1 or higher indicates healthy bone density.

Z score compares an individual's bone mineral density to that of someone of the same gender and age group. A Z-score below -2.0 suggests low bone mass or faster-than-expected bone loss [13]. It is particularly useful in identifying secondary osteoporosis in younger individuals, including children, premenopausal women, and men under 50.

The FRAX score estimates the probability of fracture over the next ten years, represented as a percentage based on data from the hip, spine, and forearm [14]. Higher FRAX scores indicate a greater risk of fracture, often prompting further treatment or diagnostic tests. Osteoporosis renders bones weak and brittle, making them susceptible to fractures even with minor strain or movement.

Osteoporosis detection utilizes various tools such as bio-sensors, physical sensors, and medical imaging technologies including X-rays, SXA/SEXA, DXA/DEXA, MRI, CT scans, and ultrasound scans [15]. However, in the medical field, the accurate assessment of osteoporosis can be challenging, often leading to either underestimation or overestimation. Presently, deep learning techniques, optimization algorithms, and image processing and analysis concepts are commonly employed for osteoporosis detection using imaging modalities. Neural network-based architectures such as CNN, U Net, and Alex Net are particularly favoured for this purpose [16]. Convolutional Neural Networks play a crucial role in automating tasks like vertebral body labelling, segmentation, and volumetric BMD calculation. Despite its widespread use, the DXA method has limitations, including susceptibility to degenerative changes like osteophytes, variations in vertebra size, and tissue non-uniformity in neighbouring areas. Researchers can adopt either prospective or retrospective study approaches to investigate osteoporosis detection methods.

Modality	**Normal Bone**	**Osteoporotic Bone**

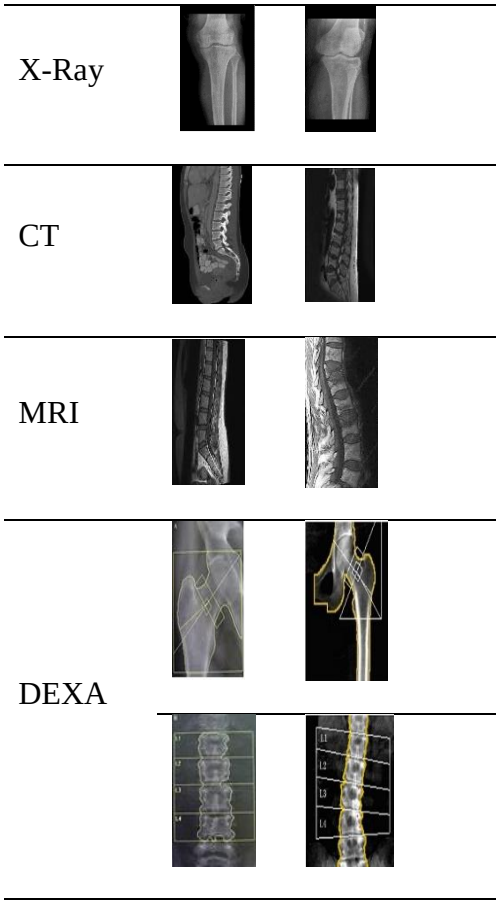


Fig. 1. Sample multimodal images of normal and OP

2. LITERATURE REVIEW

Sikkander et al. (2021) have implemented a new segmentation technique derived from 2-dimensional Local Centre of Mass computation on X-ray images of knee osteoarthritis. This technique is evaluated against other two segmentation techniques-watershed and gaussian mixed model-hidden Markov random field. Dice Score is higher and memory occupied is lesser. This technique is more suitable for the analysis of bone density.[17]

Ngyuen et al. (2021) have collected x-ray images of lower hips and applied Sobel algorithm along with Deep Neural Network derived from Convolutional Neural Networks on them. The BMD values from DEXA images are correlated with these CNN outputs. The outputs of these CNN models on three Singh sites and parameters like height, weight, age are given to Ensemble Artificial Neural Network. The high correlation coefficient and the lesser computation time acknowledges its superiority.[18]

Fathima et al. (2020) have applied Modified U-Net coupled with Attention Unit on the two datasets DEXSIT and XSITRAY having X -ray and DEXA images of bones to do accurate segmentation of bones. A linear regression method is applied to calculate BMD and T-score, which leads to the classification into Normal, Osteopenia and Osteoporosis. The results are quite impressive with respect to dice score and classification accuracy. The calculated BMD and T-Score values are validated against the respective clinical results.[19]

Zheng et al. (2021) have developed a regression method to calculate BMD from the plain X-ray images of hip on labelled images with DEXA measured BMD and unlabelled images with falsely labelled BMD.A new concept of adaptive triplet loss is introduced to increase the accuracy of this regression. BMD calculated through this method has high Pearson correlation coefficient as compared against ground truth BMDs.[20]

Singh et al. (2017) have extracted the statistical features of different orders from the X-ray images and given them as input to these 4 classifiers-SVM, KNN, Naïve Bayes, and ANN, to categorize them into normal and osteoporotic cases. The results are very impressive in the terms of accuracy and time complexity, especially for SVM.[21]

Sapthagirivasan and Anburajan (20130 have utilised kernel based SVM on the digital radiographs of hips to find trabecular features-boundness, radial bias function, orientation, solidity of delta and spur and hence find persons with low bone mineral density. The authors claim to have very high classifier accuracy and high Pearson correlation between trabecular features with age and BMD calculated through DEXA.[22]

Hussain et al. (2018) have applied a new feature extraction and selection method by the Pixel Level Decision Tree to do segmentation of femur in the DEXA images. The results achieved by this technique are assessed again 3 other medical image segmentation techniques-Global Threshold, Region Growing Threshold and Artificial Neural Networks. PLDT does the best among these in the task of segmentation on DEXA images.[23]

Mohammed et al. (2018) have experimented with ANN on the Egyptian population with and without pathology to find their BMD through features extracted from DEXA-DICOM images using Histogram and Binary algorithms. BMD estimation from binary algorithm on these DEXA-DICOM images have 100 percent classification accuracy for the ANN. [24]

Mantzaris et al. (2010) have evaluated and compared two feed forward networks Probabilistic Neural networks and Learning Vector Quantization ANN to find the chances

of osteoporosis. The PNN model is the best among these two. The ROC analysis is done to find the most important factors to calculate the likelihood of osteoporosis. Age is discovered to be the most important factor. [25]

Nikola Kirilov et al. (2021) have applied CNN on DEXA images of lumbar spine with the help of using Tensor Flow in Python to estimate BMD. The accuracy is found out using the mean absolute error and standard deviation of absolute error. The estimated accuracy is correlated with the actual ones to find the predictive accuracy.[26]

Zhao et al. (2022) are the first ones to predict osteoporosis with BMFF (lumbar bone marrow fat fraction) map on MRI and QCT images. They have applied deep learning for automated segmentation. The automated segmentation is better than manual segmentation in the terms of mean dice coefficient. The parameters to assess the prediction quality of osteoporosis and abnormal bone density are area under the curve, specificity, sensitivity and accuracy.[27]

For this retrospective HIPPA study by Ruhling et al.(2022), the subjects have undergone the contrast enhanced and non-contrast enhanced CT scans. An automated pipeline (https://anduin.bonescreen.de) is used to find vBMD. Linear Regression method was utilised to find the association of vBMD between each vertebra and clinically used mean L1 to L3 values. The results show high correlation between the two, independent of age. The vertebra specific cut off values for osteoporosis was also found. [28]

Jang et al. (2022) have used a supervised learning based deep learning algorithm to find out osteoporosis and assessed the results on the basis of sensitivity, specificity and area under the curve. The visual explanation for the algorithm to predict each category was done in the terms of gradient weighted class activation maps.[29]

Sollmann et al. (2022) have evaluated volumetric lumbar bone mineral density found from CNN based framework against the vBMD from dedicated QCT. The vBMD and Hounsfield units are found to differentiate those with and without osteoporotic vertebral fractures. They conclude that automated opportunistic osteoporosis screening on CT images seem possible with high accuracy for prevalent vertebral fractures.[30]

Caffarelli Carla et al. (2022) have used radiofrequency echo graphic multi-spectrometry (REMS)approach for finding osteoporosis, as a tool to find the quality of bones and calculate the chances of fracture independent of BMD. This seems to overcome the artifacts

while finding BMD through DXA, like osteoarthritis and vertebral fracture of lumbar spine.[31]

Li XiangWeng et al. (2022) is curious to know the predictive quality of quantitative Dixon (Q-Dixon) and intravoxel incoherent motion (IVIM) attributes to find normal BMD, osteopenia and osteoporosis in the postmenopausal females. Through the intraclass correlation coefficient (ICC), One-way ANOVA, Spearman analysis, and receiver operating characteristic curve the authors claim that the t2*-corrected Q-Dixon and reduced-FOV IVIM parameters could become new biomarkers.[32]

This is a study by James Elliott through collection of radiographs, technical attributes, imaging workflow and quantitative analysis done on archaeological human bones.[33]

Barshooi and Amirkhani (2022) have produced new x -ray images of chest with the help of augmentation and generative adversarial networks. A deeper extraction of features is done through filters - the Sobel, Laplacian of Gaussian (LoG) and the 64 Gabor filters in 8 orientations and 8 scales. The 6 deep CNNs -AlexNet, GoogleNet, VGG-19, ShuffleNet V2, DenseNet-121 and DenseNet-201 are applied. Based on the two-class classification accuracy, the proposed method using Densenet-201 is found to be the best till then to find chest covid -19.[34]

SM Nazia Fathima et al. (2019) have analysed different ways to measure BMD,T Score and Z Score from DEXA scans. They have applied clustering techniques for example k means clustering and mean shift clustering and evaluated them against each other on the basis of accuracy. A new mathematical model by the name of attribute S is introduced to measure T Score from DEXA scans and hence identify osteoporosis cases.[35]

Hussain et al. (2019) have applied deep learning semantic segmentation methods like FCN, Seg-Net, U-Net to separate femur region from soft tissue regions. Other traditional segmentation algorithms like PLDT and methods dependent on Otsu's thresholding are also implemented. These are evaluated on the context of average Jaccard Index, specificity and sensitivity. FCN has the best performance on DEXA scans.[36]

Krithika M Pai (2022) has applied automated segmentation method to find and separate brain Hemorrhage areas in CT scan slices.[37]

Magnuska et al. (2022) have applied ML methods such as YOLO v3 and VIOLA Jones to find lesions on the 8 datasets of ultrasound scans of breast cancer. The classification models are assessed on the basis of accuracy, sensitivity and specificity and area under curve. Yolo V3 is found to be the best.[38]

Jalali et al. (2022) have implemented a CNN-based method to find covid-19 from X-Ray scans of chests. They have added some novelty to the Competitive Swarm Optimizer method and implemented the same. The optimisation method is used for tuning of the hyperparameters of this CNN and attains very good classification accuracy as compared to the existing methods.[39]

Tang et al. (2020) have implemented SVM method to find osteoporosis and two miRNA signatures were developed from the same.[40]

3. OBJECTIVE

The main objectives of the research are as follows: -

I. To study various research works done on medical images of different modalities with respect to Deep Learning and Image Processing & Analysis for finding Normal and Unhealthy bones such as Osteopenia and Osteoporosis.

II. To analyse the segmentation accuracy of Modified UNet algorithm which is preceded by Median Filtering on X-ray images of bones.

III. To extract features using GLCM feature extractor and apply Modified UNet through those features to segment the abnormal bone areas or low bone mass areas on X-ray bone images.

IV. To extract features using a combination of two methods -LBP (Local Binary Pattern) and GLCM (Gray Level Co-occurrence Matrix) and apply Modified UNet for Segmentation.

V. To extract GLCM features and apply AlexNet for classification on DEXA images of bones in the spine and knee regions.

VI. To evaluate and assess these segmentation performance and classification performance on the various parameters against those of the other existing methods and datasets.

4. RESEARCH PROBLEM

To some extent, X-ray scans are helpful in the diagnosis of Normal and Unhealthy bones such as Osteopenia and Osteoporosis. Even the radiologists may struggle hard to exactly locate the unhealthy bone areas suffering from Osteopenia and Osteoporosis. A standard image analysis method available in an imaging centre cannot even segment healthy bone tissues from X-ray scans or DEXA scans. If the dataset is huge, it becomes too burdensome for a radiologist to do these manually. So, we go for finding low bone mass areas automatically from DEXA images and X-ray images. This also greatly minimises the time intended for the patient's diagnosis and treatment. These can greatly reduce the chances of fracture in men aged more than 65 years and women aged more than 50 years or post-menopausal elderly women. These need careful and timely consideration with the least possible error.

5. CONTRIBUTIONS

5.1 A Review on Automated Algorithms used For Osteoporosis Diagnosis

Studies are done on different methods to segment and find osteoporosis from X-ray scans. The different methodologies used are CLAHE, Local Centre Mass, Sobel Gradient based map, CNN, UNet, FCNN, SVM, KNN, Naive Bayes, ANN, DCNN. The results are assessed on metrics like DC, memory, Computation Time, Accuracy, Sensitivity, Specificity.

Similarly different studies are done on how to segment CT, HR-pQCT and Micro-CT images to find Osteoporosis. These are CNN, Deep CNN, UNet, KNN, SVM etc. The results are assesses based on DC, computational time, Accuracy, Area Under Curve, Recall, Precision etc.

Similarly various ways to segment MR images like DWT, multiResNet, SegNet are studied and assesses on parameters like Accuracy, Sensitivity, Distance Error Tolerance, IVD, PE, TS, AAP etc.

Similarly various ways to segment DEXA scans like Kernel SVM with RBF, Pixel label Decision Tree, Recursive Wrapper Feature Elimination, ANN, Binary Algorithm, UNet, FCNN, CNN, CNN variants etc are assessed on Accuracy, Recall, DC, Sensitivity etc.

Some other soft computing ways for segmentation depending on other factors are also discussed and studied. These methods are Feature Selection, Hybrid Genetic Swarm Fuzzy classifier, SVM, GLCM, Gabor Filter, KNN, FNN, Histogram based automatic clustering, CLAHE etc. The metrics to assess them are Accuracy, Sensitivity, Specificity, etc.

5.2 Finding Low Bone Mass in Osteoporotic X-ray Images using Deep Learning Technique

The proposed algorithm used a Gabor Filter to do texture analysis because it perceives the same way as a human visual system. A 2D Gabor Filter is a Gaussian Kernel Function multiplied by Sinusoidal plane wave. A Gabor filter is dependent upon these: -Sinusoidal Factor Wavelength, Gabor Function, Phase Offset, Standard Deviation, Spatial Aspect Ratio. Then the identification and segmentation of bone mass variation is done using modified U-Net. The UNet consists of encoder followed by a decoder. By modified UNet it is meant that, the encoder operates with the help of a pretrained classifier network like VGG or ResNet. This encodes different representations of different features at multiple levels. The decoder contains an up sampling and concatenation followed by the usual operations of convolution. Up-sampling is also called as Transposed Convolution or Up Convolution or Deconvolution. The main ways to do up sampling are Nearest Neighbour, Bilinear Interpolation or Transposed Convolution. By the expansion of dimensions of features, this restores the condensed feature map to the actual size of the input image. This filter and modified UNet have never been applied previously on the medical bone images to find low bone mass variation. The results of segmentation are evaluated on these parameters-Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), Tanimoto Coefficient (TC), Dice Overlapping Index (DOI) and Computational Time.

Table 1. Performance metric values

Image Number	MSE	PSNR	TC	DOI	Time
1	0.1496	56.4169	64.1670	80.7917	9.90
2	0.1186	57.4251	63.5875	84.4550	9.72
3	0.1017	58.0919	64.0998	85.9609	8.39

4	0.1919	55.3336	63.4784	83.3583	8.20
5	0.1963	55.2356	62.0269	82.8838	8.38

Input Image	**Pre-processed Image**	**Output Image**

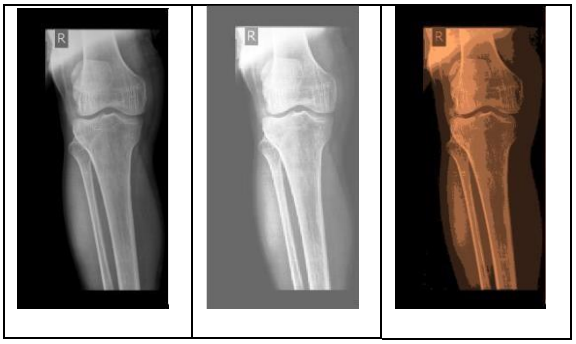
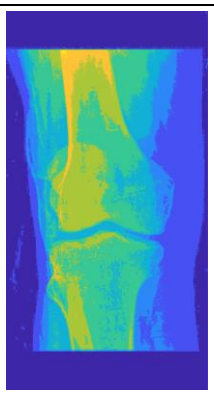


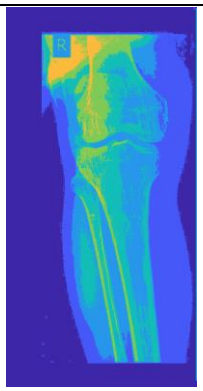
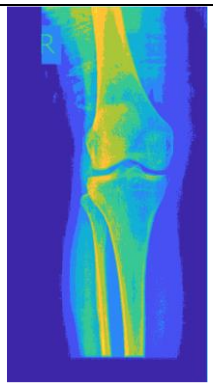
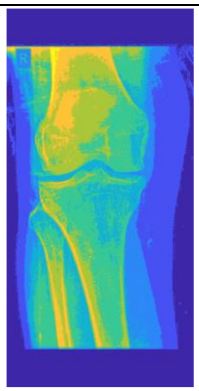
Figure 2. Proposed method outcomes

5.3 Methodological Intervention for prediction of Bone Health for Clinical Recommendation with the Help of LMGU-Net

The proposed algorithm applied Gaussian Filter as a preprocessing step and on the output of this filter Local Binary Pattern (LBP) Operator is applied to define local texture structures. On the output of this LBP operator, the Gray Level Co-Occurrence Matrix (GLCM) is applied to measure the entropy. Further, to avoid negative entropies, the GLCM is normalized. Ultimately, a modified UNet for segmentation and classification is applied. By modified UNet, It is meant that Parametric Rectified Linear Unit activation is applied instead of Rectified Linear Unit (ReLU) for measuring the non-linearity among the layers. Finally, the bone mass variation has been identified by developed algorithm. PreLU was developed to overcome the drawbacks of ReLU non linearity. PReLU tries to solve the dying ReLU issue by forming a small negative slope. PReLU has non-constant factors in its negative region, which the model learns adaptively. These techniques have never been applied earlier on the medical bone images to find low bone mass variation. The results of segmentation and classification are evaluated based on these parameters-Computational Time, Mean Squared Error (MSE), Peak Signal To Noise Ratio (PSNR), Tanimoto Coefficient Index (TC), Dice Similarity Coefficient, Accuracy, Recall/Sensitivity and Specificity.

Image Number	Input Image	Gaussian Filtered Image	Output Image	Gold standard images

1				
2				
3				
4				

5				
6				
7				
8				

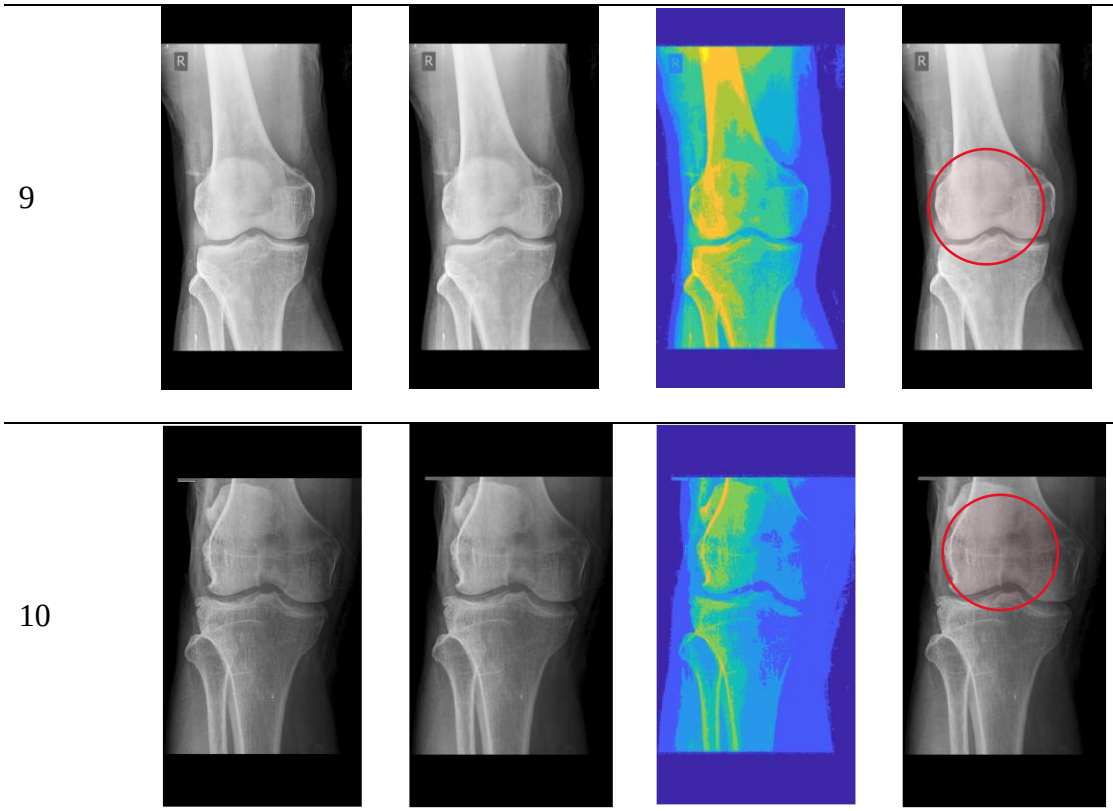


Figure 7. Classification of variation in bone mass using LGMU-net algorithm

Table 2. Performance metric values of the proposed algorithm

Image Number	Mean Squared Error (MSE)	Peak Signal to Noise Ratio (PSNR in dB)	Tanimoto Coefficient Indes (TC in %)	Dice Score (DSC in %)	Computational Time (Seconds)
1	0.0316	63.1320	70.5669	86.8168	7.24
2	0.0208	64.9592	71.5761	90.6056	7.85
3	0.0271	63.8056	71.7854	88.1191	6.31
4	0.0060	70.3839	68.4005	90.6374	7.39
5	0.0213	64.8447	69.9718	87.7445	6.67
6	0.0324	63.0286	72.5999	85.4104	6.62
7	0.0277	63.6999	74.3214	86.2765	8.08
8	0.0320	63.0795	71.0039	89.4626	7.66
9	0.0131	66.9434	72.8611	88.5542	8.10
10	0.0142	64.8454	73.8698	87.7782	6.79

6. CONCLUSION

The proposed Soft Computing approaches-based algorithms helps in processing in processing multimodal bone images like X-rays and DEXA with complications, such as noise interventions, intensity inhomogeneity and low bone mass areas. The healthy bone areas and abnormal bone regions in the input images were clearly segmented and verified with the corresponding ground truth images to measure the similarity. The developed Algorithms like modified UNet etc worked well on images of different shapes and locations with low bone mass area(s). The segmentation results clearly indicate the low bone mass areas within a a considerable time limit, which can be lowered further by tuning/adjusting various Hyper tuning parameters. Such convincing results could pave the way for the diagnosis of patients with osteopenia or osteoporotic complaints. Incorporation of the proposed methodology into clinical interventions could allow accurate inference of the degree of discomfort during pre- and post – treatment, leading to faster and more accurate treatment of patients.

7. ORGANIZATION OF THE THESIS

The thesis is organized as the follows: The significant detection of low bone mass areas as well as the major contribution of X-ray scans and DEXA scans of various human bone areas to segment and diagnose those abnormalities in bone mass variation, have been explained in the Chapter 1.

Chapter 2 gives a brief overview of various X-ray and DEXA bone segmentation algorithms and their impact on the medical image analysis. The scope and aspirations of this thesis are extensively described. Chapter 3 describes data acquisitions from hospitals and Kaggle websites with low bone mass areas and high bone mass areas.

Chapter 4 discusses the soft computing approaches used in this research for X-ray and DEXA bone image segmentation. Chapter 5 explains how preprocessing steps and feature extractions influence deep learning-based segmentation & classification strategies used in this study to segment X-Ray and DEXA bone images. Chapter 6 outlines the functioning and outcomes of GLCM-Modified UNet, LBP-GLCM-Modified UNet etc algorithms. Chapter 7 concludes the research work and discusses the efforts made in this study as well as the best segmentation and classification algorithm for X-ray and DEXA images among these ones, The Research work concludes with the revelation of future works and future investigation. The references of all these hybrid algorithms that are employed for the

segmentation and classification of X-ray and DEXA bone images in this research work are enlisted.

8. REFERENCES

1. Lorentzon, M., H. Johansson, N. C. Harvey, E. Liu, Lisbeth Vandenput, E. V. McCloskey, and J. A. Kanis. "Osteoporosis and fractures in women: the burden of disease." *Climacteric* 25, no. 1 (2022): 4-10.
2. Vilaca, Tatiane, Richard Eastell, and Marian Schini. "Osteoporosis in men." The Lancet Diabetes & Endocrinology (2022).
3. Bente L. Langdahl, "Overview of treatment approaches to osteoporosis" The British Pharmacological Society,1–16, 2020.
4. Anika K. Anam and Karl Insogna "Update on Osteoporosis Screening and Management" Volume 105, Issue 6, P1117-1134, November 01, 2021.
5. Bente L. Langdahl, "Overview of treatment approaches to osteoporosis" The British Pharmacological Society,1–16, 2020.
6. Anna C. van der Burgh, Catherine E. de Keyser, M. Carola Zillikens, and Bruno H. Stricker, "The Efects of Osteoporotic and Non osteoporotic Medications on Fracture Risk and Bone Mineral Density" The Effects of Osteoporotic and Non-osteoporotic Medications on Fracture Risk and Bone Mineral Density, Drugs, 81, 1831–1858, 2021.
7. Gregson, Celia L., David J. Armstrong, Jean Bowden, Cyrus Cooper, John Edwards, Neil JL Gittoes, Nicholas Harvey et al. "UK clinical guideline for the prevention and treatment of osteoporosis." *Archives of osteoporosis* 17, no. 1 (2022): 1-46.
8. Conradie, Magda, and T. de Villiers. "Premenopausal osteoporosis." *Climacteric* 25, no. 1 (2022): 73-80.
9. Bimal, Gayathri, Joanne Sahhar, Monika Savanur, and Gene-Siew Ngian. "Screening rates and prevalence of osteoporosis in a real-world, Australian systemic sclerosis cohort." *International journal of rheumatic diseases* 25, no. 2 (2022): 175-181.
10. Gold, L. S., Cody, R. F., Tan, W. K., Marcum, Z. A., Meier, E. N., Sherman, K. J., ... & Jarvik, J. G. (2022). Osteoporosis identification among previously undiagnosed individuals with vertebral fractures. Osteoporosis International, 1-11.

11. Godos, Justyna, Francesca Giampieri, Emanuele Chisari, Agnieszka Micek, Nadia Paladino, Tamara Y. Forbes-Hernández, José L. Quiles et al. "Alcohol Consumption, Bone Mineral Density, and Risk of Osteoporotic Fractures: A Dose–Response Meta-Analysis." *International Journal of Environmental Research and Public Health* 19, no. 3 (2022): 1515.
12. Zhu, Kun, Michael Hunter, Bronwyn GA Stuckey, and John P. Walsh. "Establishing a Total Hip T-Score Threshold to Measure Contralateral Hip Bone Mineral Density: Avoiding Missed Diagnosis of Osteoporosis." *Journal of Clinical Densitometry* (2022).
13. Anabtawi, A., M. Holyoak, J. He, E. Cristiano, D. Polineni, and L. Graves. "Trabecular bone score in people with cystic fibrosis." *Osteoporosis International* (2022): 1-9.
14. Johansson, Lisa, H. Johansson, Kristian F. Axelsson, H. Litsne, N. C. Harvey, E. Liu, W. D. Leslie et al. "Improved fracture risk prediction by adding VFA-identified vertebral fracture data to BMD by DXA and clinical risk factors used in FRAX." *Osteoporosis International* (2022): 1-14.
15. Martel, Dimitri, Anmol Monga, and Gregory Chang. "Osteoporosis Imaging." *Radiologic Clinics* (2022).
16. Ramaraj, K., Govindaraj, V., Zhang, Y. D., Murugan, P. R., Wang, S. H., Thiyagarajan, A., & Sankaran, S. (2022). Agnostic multimodal brain anomalies detection using a novel single-structured framework for better patient diagnosis and therapeutic planning in clinical oncology. Biomedical Signal Processing and Control, 77, 103786.
17. Mohamed Yacin Sikkandar, S. Sabarunisha Begum, Abdulaziz A. Alkathiry, Mashhor Shlwan N. Alotaibi, Md Dilsad Manzar and Mohamed Abdelkader Aboamer “Segmentation of human knee osteoarthritis images using unsupervised local center of mass computation technique” Journal of Ambient Intelligence and Humanized Computing, 2021.
18. Thong Phi Nguyen, Dong-Sik Chae, Sung-Jun Park, and Jonghun Yoon “A novel approach for evaluating bone mineral density of hips based on Sobel gradient-based map of radiographs utilizing convolutional neural network” Computers in Biology and Medicine, Vol. 132, 2021.

19. S.M. Nazia Fathima, R. Tamilselvi, M. Parisa Beham and D. Sabarinathan "Diagnosis of Osteoporosis using modified U-net architecture with attention unit in DEXA and X-ray images" Journal of X-Ray Science and Technology, 2020.
20. Kang Zheng, Yirui Wang, Xiao-Yun Zhou, Fakai Wang, Le Lu, Chihung Lin, Lingyun Huang, Guotong Xie, Jing Xiao, Chang-Fu Kuo, and Shun Miao "Semi-Supervised Learning for Bone Mineral Density Estimation in Hip X-ray Images" 2021.
21. Anushikha Singh, Malay Kishore Dutta, Rachid Jennane, and Eric Lespessailles "Classification of the trabecular bone structure of osteoporotic patients using machine vision" Computers in Biology and Medicine, 2017.
22. V. Sapthagirivasan and M. Anburajan, "Diagnosis of osteoporosis by extraction of trabecular features from hip radiographs using support vector machine: An investigation panorama with DXA" Computers in Biology and Medicine, 43 (2013) 1910–1919.
23. Dildar Hussain, Mugahed A. Al-antari, Mohammed A. Al-masni, Seung-Moo Han and Tae-Seong Kim, "Femur segmentation in DXA imaging using a machine learning decision tree", Journal of X-Ray Science and Technology, vol. 26, no. 5, pp. 727-746, 2018.
24. Ehab I. Mohamed, Radwa A. Meshref, Samir M. Abdel-Mageed, Moustafa H. Moustafa, Mohamed I. Badawi, and Samy H. Darwish "A Novel Morphological Analysis of DXA-DICOM Images by Artificial Neural Networks for Estimating Bone Mineral Density in Health and Disease" Journal of Clinical Densitometry, 2018.
25. Dimitrios Mantzaris, George Anastassopoulos, Lazaros Iliadis, Konstantinos Kazakos, and Harris Papadopoulos "A soft computing approach for osteoporosis risk factor estimation" International Federation for Information Processing, 2010.
26. Nikola Kirilov, Elena Kirilova, and Evgeniy Krastev "Using Machine Learning to Predict Bone Mineral Density from Dual-energy X-ray Absorptiometry Images of the Lumbar Spine" 2021.
27. Zhao, Yinxia, Tianyun Zhao, Shenglan Chen, Xintao Zhang, Mario Serrano Sosa, Jin Liu, Xianfu Mo et al. "Fully automated radiomic screening pipeline for osteoporosis and abnormal bone density with a deep learning-based segmentation using a short lumbar mDixon sequence." Quantitative Imaging in Medicine and Surgery 12, no. 2 (2022): 1198.

28. Rühling, Sebastian, Andreas Scharr, Nico Sollmann, Maria Wostrack, Maximilian T.Löffler, Bjoern Menze, Anjany Sekuboyina et al. "Proposed diagnostic volumetric bone mineral density thresholds for osteoporosis and osteopenia at the cervicothoracic spine in correlation to the lumbar spine." European Radiology (2022): 1-8.
29. Jang, Miso, Mingyu Kim, Sung Jin Bae, Seung Hun Lee, Jung-Min Koh, and Namkug Kim. "Opportunistic osteoporosis screening using chest radiographs with deep learning: Development and external validation with a cohort dataset." Journal of Bone and Mineral Research 37, no. 2 (2022): 369-377.
30. Sollmann, Nico, Maximilian T. Löffler, Malek El Husseini, Anjany Sekuboyina, Michael Dieckmeyer, Sebastian Rühling, Claus Zimmer et al. "Automated opportunistic osteoporosis screening in routine computed tomography of the spine–comparison with dedicated quantitative CT." Journal of Bone and Mineral Research (2022).
31. Caffarelli, Carla, Maria Dea Tomai Pitinca, Antonella Al Refaie, Michela De Vita, Simone Catapano, and Stefano Gonnelli. "Could radiofrequency echographic multispectrometry (REMS) overcome the overestimation in BMD by dual-energy X-ray absorptiometry (DXA) at the lumbar spine?." BMC Musculoskeletal Disorders 23, no. 1 (2022): 1-8.
32. Li, Xiangwen, Rong Lu, Yuxue Xie, Qing Li, Hongyue Tao, and Shuang Chen. "Identification of abnormal BMD and osteoporosis in postmenopausal women with T2*-corrected Q-Dixon and reducedFOV IVIM: correlation with QCT." European Radiology (2022): 111.
33. Elliott, James. "Radiographic Technique for Archaeological Human Dry Bones: a scoping review."
34. Barshooi, A. H., & Amirkhani, A. (2022). A novel data augmentation based on Gabor filter and convolutional deep learning for improving the classification of COVID-19 chest X-Ray images. Biomedical Signal Processing and Control, 72, 103326.
35. Fathima, SM Nazia, R. Tamil Selvi, and M. Parisa Beham. "Assessment of BMD and Statistical Analysis for Osteoporosis Detection." Biomedical and Pharmacology Journal 12, no. 4 (2019): 1907-1914.

36. Hussain, Dildar, Rizwan Ali Naqvi, Woong-Kee Loh, and Jooyoung Lee. "Deep Learning in DXA Image Segmentation." Computers, Materials and Continua 66(3):2587-2598 (2021).
37. Pai, Krithika M. "Region Detection and Segmentation of Brain Hemorrhage using Algorithmic Approach of Image Processing." In Journal of Physics: Conference Series, vol. 2161, no. 1, p. 012070. IOP Publishing, 2022.
38. Magnuska, Zuzanna Anna, Benjamin Theek, Milita Darguzyte, Moritz Palmowski, Elmar Stickeler, Volkmar Schulz, and Fabian Kießling. "Influence of the Computer-Aided Decision Support System Design on Ultrasound-Based Breast Cancer Classification." Cancers 14, no. 2 (2022): 277.
39. Jalali, S. M. J., Ahmadian, M., Ahmadian, S., Hedjam, R., Khosravi, A., & Nahavandi, S. (2022). X-ray image based COVID-19 detection using evolutionary deep learning approach. Expert Systems with Applications, 116942.
40. Tang, X., Bai, Y., Zhang, Z., Lu, J."A validated miRNA signature for the diagnosis of osteoporosis related fractures using SVM algorithm classification". Experimental and Therapeutic Medicine 20, no. 3 (2020): 2209-2217.

List of Publications

1. Amiya, G., Ramaraj, K., Murugan, P. R., Govindaraj, V., Vasudevan, M., & Thiyagarajan, A. (2022). A review on automated algorithms used for osteoporosis diagnosis. *Inventive Systems and Control: Proceedings of ICISC 2022*, 247-262.
2. Amiya, G., Ramaraj, K., Murugan, P. R., Govindaraj, V., Vasudevan, M., & Thiyagarajan, A. (2022, December). Assertion of Low Bone Mass in Osteoporotic X-ray images using Deep Learning Technique. In *2022 4th International Conference on Advances in Computing, Communication Control and Networking (ICAC3N)* (pp. 830-835). IEEE.
3. Amiya, G., Murugan, P.R., Ramaraj, K., Govindaraj, V., Vasudevan, M., Thirumurugan, M., Abdullah, S.S. and Thiyagarajan, A., 2024. LMGU-NET: methodological intervention for prediction of bone health for clinical recommendations. *The Journal of Supercomputing*, pp.1-28.
4. Amiya, G., Murugan, P.R., Ramaraj, K., Govindaraj, V., Vasudevan, M., Thirumurugan, M., Zhang, Y.D., Abdullah, S.S. and Thiyagarajan, A., 2024. Expeditious detection and segmentation of bone mass variation in DEXA images using the hybrid GLCM-AlexNet approach. *Soft Computing*, pp.1-14.